Optimised Fracture Network Model for Habanero Reservoir

Chaoshui Xu*, School of Civil, Environmental and Mining Engineering, University of Adelaide
Peter Dowd, Faculty of Engineering, Computer and Mathematical Sciences, University of Adelaide
Doone Wyborn, Geodynamics Limited

Abstract:

Fracture networks and their connectivity are the principal factors affecting fluid flow in hot dry rock (HDR) geothermal reservoirs. Largely because of the complexity of the problem models of HDR reservoirs tend to be over-simplified using either a very limited number of fractures or an equivalent porous media approach. This paper describes a Markov Chain Monte Carlo (MCMC) conditioning technique for reservoir fracture modelling by taking into account the seismic events collected during the fracture stimulation process. Using the technique, the fracture model "evolves" during the simulation process and eventually converges to a predefined optimal criterion. The proposed method is tested using seismic data collected during the hydraulic fracture stimulation processes of the Habanero wells in Geodynamics' Cooper Basin project.

Keywords: Fracture network, seismic events, Markov chain Monte Carlo.

Introduction

The technical and commercial viability of HDR geothermal energy depends on the creation of artificial reservoirs, or Enhanced Geothermal Systems (EGS), in the rock mass by stimulating and creating fractures (generally by hydro-fracturing) to enable geothermal flow. The artificial reservoir forms the critical component in an EGS: the fracture network that connects the injection and production wells and acts as the heat exchange chamber for the system. HDR productivity depends crucially on the connectivity/permeability of the reservoir fracture network and a realistic fracture model, such as that described in this paper, is the key to assessing reservoir performance and designing a suitable heat exchange chamber for the EGS.

The characterisation of rock fracture networks is a very difficult problem not least because accurate field measurement of a single fracture is difficult and measurement of all fractures is impossible. Thus, in practice, the whole fracture system is not observable on any meaningful scale and the only realistic approach is via a stochastic model informed by sparse data and/or by analogues. In HDR applications, a realistic solution is even more difficult as the only reference data related to the fracture system are either from geophysical borehole logs and/or sparse seismic events kilometres beneath the surface and detected during the hydraulic stimulation process. For these reasons current models of fracture systems used for HDR flow modelling are oversimplified representations of reality. They either use an equivalent porous media approach (e.g., Xing et al. 2009), single fracture representation (e.g., Zhang et al., 2009) or a combination of both.

Stochastic fracture modelling is the general approach in which locations, size, orientation and other properties of fractures are treated as random variables with inferred probability distributions. In the simplest case, once the parameters of the distributions are inferred, the rock fracture model is constructed by Monte Carlo simulation. First, the fracture locations are generated, usually by a Poisson distribution in which fracture intensity for a particular area is either assumed to be constant or is derived from geostatistical estimation or simulation. Secondly, the orientation of each fracture is generated, most commonly from a Fisher distribution. Finally, the size of each fracture is generated from a specified distribution, the most common being exponential, lognormal or gamma. Other fracture properties, such as aperture width and fracture strength, can then be added into the network by additional Monte Carlo steps. Options for fracture intersections and fracture termination can also be incorporated. Simulated fracture models are usually validated by sampling the model (using scan lines or areas) and assessing the extent to which the sampled values conform to the statistical models specified (Kulatilake et al. 2003). Such models are certainly very useful in describing the statistical behaviours of the fracture system. However, in order to make the generated models more realistic, some forms of data conditioning must be built into the fracture generation process. Data conditioning in two-dimensional fracture trace simulation is generally considered a simple matter but, probably because of the complexity involved, there are very few publications of algorithms and methods for data conditioning in three-dimensional stochastic fracture modelling. Mardia et. al (2007) described an attempt to condition a fracture model by borehole intersection data using Markov Chain Monte Carlo (MCMC) simulation. In this paper, however, the conditioning data are the seismic events observed during the fracture stimulation process of the HDR reservoir and they are not, therefore, confined to any known order (e.g., boreholes).

During hydraulic stimulation, fracture slips/initiations/propagations produce microseismic events that can be monitored by a network of geophones and analysed to obtain the event locations. To date, these "point cloud" data have been used to estimate the volume of a reservoir that is connected by wells. We believe these micro-seismic events not only identify the locations of fracture slip, initiation and/or propagation but also contain vital information about the structure of existing fractures and fracture networks. Successful extraction of this information will significantly improve the reliability of fracture models so that a more realistic fracture representation of the HDR reservoir can be obtained. Moriya et al. (2002) use microseismic multiplet analysis to derive the fracture plane on the assumption that seismic events from the same fracture will produce similar microseismicities. This approach, however, only accounts for a small proportion of the total seismic events (17% in Moriya et al. 2002) and the fundamental assumption behind the approach is questionable.

Assumption

It is generally acknowledged that during the hydraulic fracture stimulation process, the effective normal compressive stress acting across two fracture planes of a fracture is reduced due to the hydraulic pressure and that will cause the two planes to slip against each other. This is generally considered to be the key mechanism in creating a permeable HDR reservoir as shear-slips will result in mis-alignment of fracture surface topographies which will cause a lateral dilation and thereby enhance fracture apertures and significantly increase the permeability of the fracture network. The shear slips between fracture planes will produce small-scale seismicity whose seismic waves can be captured and analysed by a network of geophones to derive the location of the event (Baisch et al. 2006). The effect of hydraulic pressure also makes it possible for existing fractures to propagate in the reservoir and new fractures to be initiated. The final outcome of the process will be a permeable reservoir connected to the wells through a complex fracture network.

Based on this conceptual description of the fracture stimulation process, it is reasonable to assume that seismic events only occur on fracture planes. The criterion of a realistic fracture model is then directly related to the overall closeness of the seismic events to fracture planes fitted in the model. In this context, fracture simulation essentially becomes a stochastic geometry reconstruction problem given a set of point clouds. Reconstruction of a surface from random point clouds is computationally and algorithmically challenging and is an active research area in computer and mathematical sciences (Bercovier et al. 2002). The success of current practice, however, depends critically on close sampling points on the surface, which is usually not an issue as the point clouds are generally obtained from laser scanning or some form of digitizing. For seismic point clouds in geothermal applications, however, samples are very sparse. For a given fracture, only a few points are available, which indicate either the propagation front of the fracture or a point on the fracture surface where shear slip occurs at the time the events are detected. Current methodology is thus not directly applicable to fracture modelling.

The most common approach in stochastic fracture modelling is to use a 3D plane to represent a fracture, which could be bounded (e.g., elliptical plane, polygonal plane) or unbounded (e.g., Poisson plane). The fracture model (network) then becomes a series of connected fracture planes, F_i, i=1,2…n, where n is the total number of fractures. A seismic event point, P_j, j=1,2..m (m is the total number of seismic event points) can then be associated with a fracture F_i with distance $d_{j:i}$. $\sum_{j=1}^{m} d_{j:i}^2$ can then be used as a simple criterion to quantify the goodness of fit of the fitted fracture model.

MCMC model

Planar polygons are used to represent fractures in this research. For each fracture polygon F_i, the location is described by the coordinates of its centre point (x_i, y_i, z_i), the orientations are described by three angles: dip direction α_i, dip angle β_i and rotation angle γ_i and the sizes of the fractures are described by a major axis a_i and a minor axis b_i of an ellipse containing the polygon (Xu & Dowd, 2010). In other words, we parameterize fracture planes with parameters (x_i, y_i, z_i, α_i, β_i, γ_i, a_i, b_i), $i=1,2…n$. Fracture plane F_i can also be expressed in functional form as $\lambda_x^{(i)}x + \lambda_y^{(i)}y + \lambda_z^{(i)}z = \omega^{(i)}$ where $(\lambda_x^{(i)}, \lambda_y^{(i)}, \lambda_z^{(i)})$ is the unit vector normal to the fracture plane and can be calculated from (α_i, β_i, γ_i). Given a point P_j (x_j, y_j, z_j), not necessarily lying on the plane, the signed orthogonal distance to fracture F_i is defined by:

$$d_{j:i} = \begin{cases} \lambda_x^{(i)}x_j + \lambda_y^{(i)}y_j + \lambda_z^{(i)}z_j - \omega^{(i)} & if \ P_j^{(F_i)} \in F_i \\ \infty \quad otherwise \end{cases} \tag{1}$$

where $P_j^{(F_i)}$ is the projection point of P_j on fracture plane F_i. A matching function $\xi(j)\in\{1,2,\ldots,n\}$ is used to associate each point P_j with one and only one fracture polygon. We shall impose a simple criterion of minimum distance for this association and therefore by writing $d_{j:i}$ we mean point P_j is associated with fracture polygon F_i as its distance calculated by Equation (1) is the minimum when compared with distances to any other fracture plane.

$d=\{d_{j:i}\}\forall j$ is then the complete set of projection distances. Since seismic event points that lie on the same fracture will not be exactly co-planar, we must allow for statistical variation and treat a fracture as a distorted version of an idealized plane. A simple Gaussian noise model can then be adopted:

$$d_{j:i} \sim N(0,\sigma^2) \qquad (2)$$

to represent the distortion in the data from the idealized plane. In other words, the orthogonal distances are identically and independently normally distributed with mean zero and variance σ^2. Therefore, the likelihood function for the set of seismic event points $P=\{P_j\}$ can be defined as:

$$L(P;F,\xi)=\left(\frac{1}{\sqrt{2\pi}\sigma}\right)^m \prod_{j=1}^{m} e^{-\frac{(d_{j:i})^2}{2\sigma^2}} \qquad (3)$$

given a set of fractures $F=\{F_i\}$ and the matching function $\xi(.)$. The product of this likelihood with priors of F gives the posterior distribution for F and the attention now is to estimate the posterior distributions of F and hence the parameters of the fracture set. A Markov chain can be used to generate samples from the posterior distribution which is commonly constructed by the Metropolis-Hastings algorithm using the Monte Carlo acceptance/rejection technique imposed by the Hastings' ratio:

$$\varepsilon\left(F^{(t)},P\right)=\min\left\{1,\frac{\delta(P)q(F^{(t)}\mid P)}{\delta(F^{(t)})q(P\mid F^{(t)})}\right\} \qquad (4)$$

where $\delta(.)$ is the posterior (target) distribution and $q(.)$ is a transition kernel which is usually chosen so that it is easy to sample from.

A more detailed description of this model can be found in Mardia et al (2007) where a similar model was developed to generate fracture models conditional on intersection points between fractures and boreholes drilled on a regular grid.

The Habanero Point Cloud

The point cloud used in this study is the Q-Con processed dataset of locations of seismic events recorded during the hydraulic fracture stimulation of Habanero 1 between November 6 and December 22, 2003 (Weidler, 2005). A total of 23,232 seismic events are recorded in this dataset which covers an area roughly of 2.5 km^2. Figure 1 shows the absolute hypocentre locations of these events.

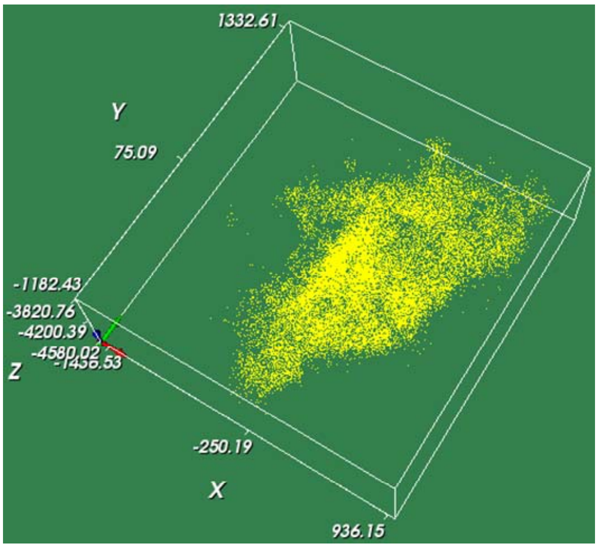


Figure 1 Absolute hypocenter locations of the seismic events

Clearly an ideal sub-horizontal reservoir has been formed by the stimulation process which is gently dipping in the South-west direction. Early analysis has revealed that the major part of the reservoir is confined within a sub-horizontal layer of approximately 30m (Baisch et al. 2006). Figure 2 shows ratios of increments in the volume of the reservoir, the geographical extents in the horizontal, East-west and North-south vertical planes covered by the seismic events during the stimulation period. Note that the increments are plotted on a relative scale where the ordinate represents the ratios against the volume or geographical extents of the reservoir covered by seismic events on November 6, 2003.

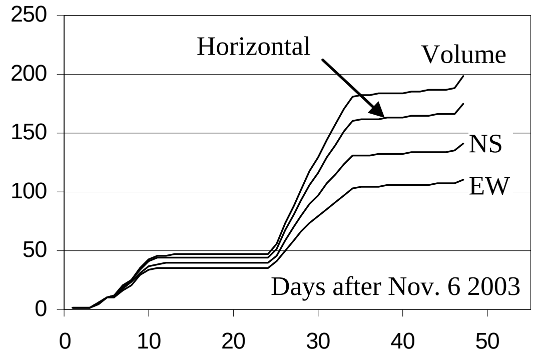


Figure 2 Increments in volume and geographical extents covered by seismic events

Habanero Fracture Model

A total of 20052 fractures were initially generated based on a non-homogeneous point process with a non-parametric density model estimated by the point cloud shown in Figure 1. Fracture locations (x_i, y_i, z_i), i=1,…,20052, are generated. The following parameters are used for initial fracture generation:

- Fracture orientation: Fisher distribution with κ=1. Orientation parameters (α_i, β_i, γ_i) are then calculated.
- Fracture size: lognormal distribution with mean = 80m and variance = 12,000 m^2.

MCMC method described was then applied to update the fracture network. The following transition kernels are used in the MCMC process:

- Fracture orientation (α_i, β_i, γ_i): normal proposal with standard deviation of 0.1 (in radian).
- Fracture location (x_i, y_i, z_i): normal proposal with standard deviation of 1.0.

Fracture size is not optimised in the current trial. Fractures without any association with any point after 100,000 iterations were removed from the system. After 2M iterations, the fracture model obtained is shown in Figure 3.

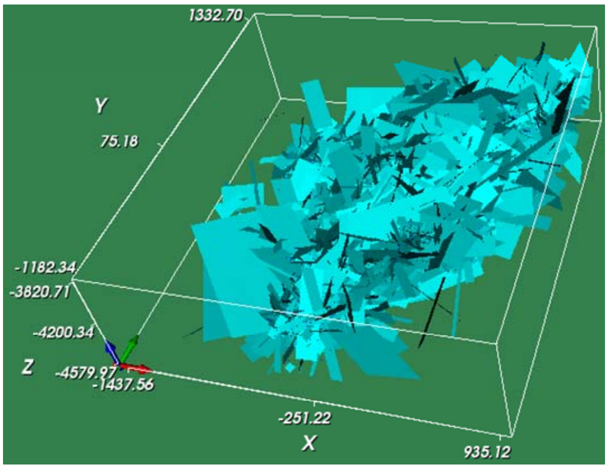


Figure 3 Habanero fracture model after 2M MCMC steps

This fracture model includes 10,995 fractures. Figure 4 shows the distribution of $d_{j:i}$ before and after the application of the MCMC updating process. Comparison of statistics is given in Table 1. Clearly the reliability of the model has been significantly improved.

Table 1 Comparison of statistics of $d_{j:i}$ before and after MCMC optimisation

	Initial model	Optimised model
Number of fractures	20052	10995
Minimum $d_{j:i}$	-116	-0.35
Maximum $d_{j:i}$	303	0.39
Mean value of $d_{j:i}$	0	0
Variance of $d_{j:i}$	12.5	0.0028
$\sum d_{j:i}^2$	291437	66
99% of $d_{j:i}$ within range	[-11, 34]	[-0.17, 0.17]

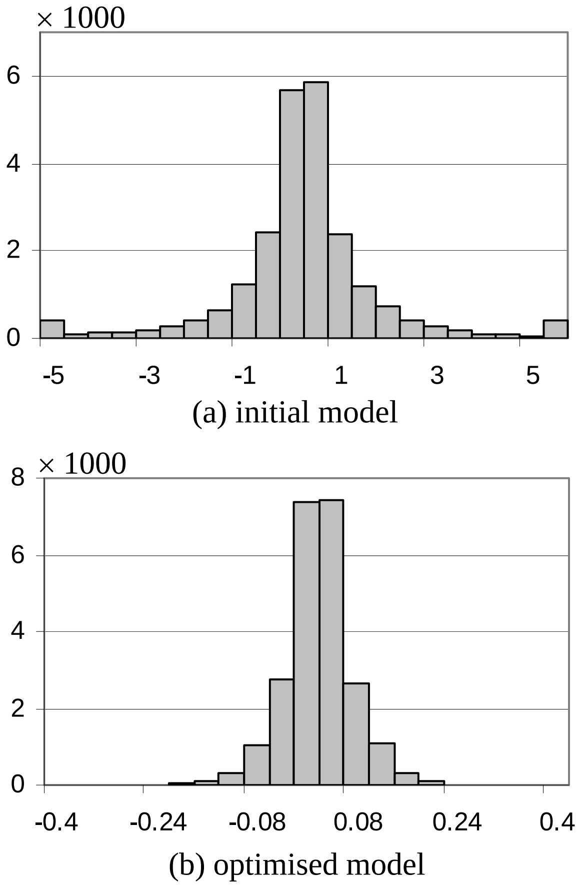
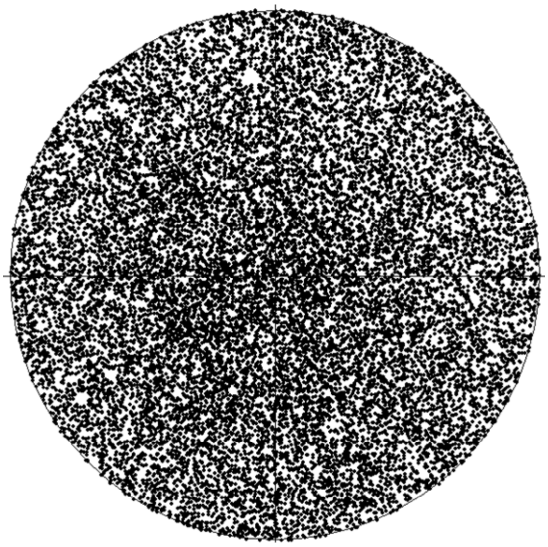
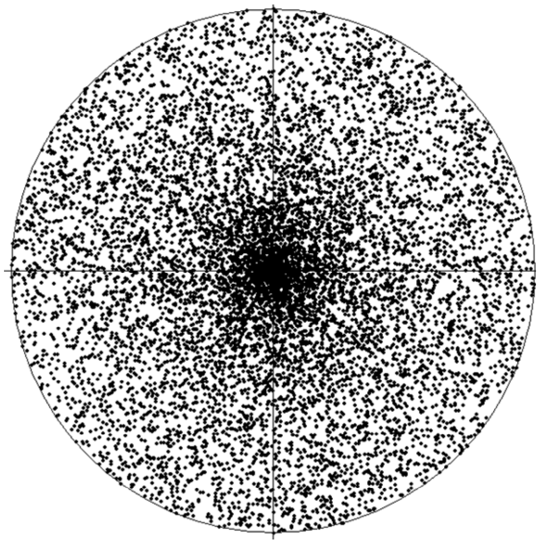


Figure 4 Histogram of $d_{j:i}$ for intial and optimised fracture models

Orientations of fractures have also changed significantly. There is no clear indication of orientation preference in the original fracture model (see the lower hemispherical projections of poles of fracture planes in Figure 5a). The fracture pole plot after optimisation (Figure 5b) clearly demonstrates a great proportion of sub-horizontal fractures. This is encouraging as it agrees well with the propagation pattern of the seismic event point cloud observed during stimulation (Baisch et al. 2006).



(a) initial model



(b) optimised model

Figure 5 Hemispherical projections of poles of fracture planes

Conclusions

This is a preliminary trial to demonstrate the application of MCMC in fitting a fracture model using a point cloud dataset. Clearly the method is effective, however there are still many remaining challenging issues. Fracture join/split (Mardia et al. 2007) is not yet considered in this work. The effect of the initial point process model has not been assessed and this will affect the total number of fractures retained in the final fracture network. The illustrated fracture model is by no means the ultimate optimal model for the Habanero fractured reservoir and further investigation is needed to achieve such a model.

The next stage of the process is to assess the connectivity of the fracture network between wells (e.g., between Habanero 1 and 3). Hydraulic apertures of fractures can be estimated from the degree of seismicity recorded in the seismic signals (Baisch et al. 2009). The hydraulic conductance between wells can then be estimated.

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